##

Project Title

Towards 10-minute Magnetic Resonance Imaging scans in children with machine learning

Project Summary

Magnetic Resonance Imaging (MRI) enables diagnosis and monitoring of many childhood diseases. MRIs produce good-quality images of many parts of the body (including the heart and abdomen), without the need for ionising radiation. However, MRIs are challenging in children, as they are time consuming (~1 hour to perform) and require patient cooperation. Hence it is necessary to use general anesthesia in children <8 years of age, which is costly and carries some risk.

One way of overcoming these problems is to speed up the acquisition of MRI data. The simplest way is to reduce the amount of data acquired (data undersampling). Unfortunately, this results in artefacts that make the images unusable. Additionally, as each image is acquired over tens-of-seconds to several minutes, bulk motion and respiratory motion can degrade image quality. Current reconstruction methods for removing these artefacts, allow limited acceleration, or use time consuming algorithms, hampering their clinical uptake. A new approach is Machine Learning that aims to optimise data undersampling and efficient acquisition by 'learning' how to remove undersampling and motion artefacts. This project aims to incorporate ML into the reconstruction of highly undersampled paediatric MR data acquired in the abdomen. This will allow scan times to be massively reduced in paediatric diseases.

Project Background and Significance

Magnetic Resonance Imaging (MRI) scans play a vital role in diagnosing and monitoring many abdomen diseases in children. However they take a long time (often over an hour) and require patient cooperation, which means that this important tool is only available in specialist centres. One way of overcoming these problems would be to speed up the MRI scans so the children do not have to keep still or hold their breath. The simplest way of doing this is to speed up data acquisition, i.e collect less data, but this can cause distortion in the images so that they cannot be used. Our current ways of converting these into useful images, but these are complicated and take too long to use in a hospital setting.

Machine Learning (ML) has been successfully used for analysing many types of images, however only a few studies have shown its potential for reconstruction of MRI images. In this project we will develop ML techniques to reconstruct MRI images from abdominal MRIs in children.

This will enable fast reconstructions, with equivalent/better image quality than conventional state-of-the-art techniques. These could enable scan times of ~10 minutes, making MRIs less difficult for children, potentially eliminating the need for general anaesthesia or breath holding techniques, and would have a significant impact on reducing waiting lists and costs for the NHS. It would also mean that MRI scanning would be used far more often, so it could help many more children.

Project Aims and Objectives

The overall objective of this study is to develop novel accelerated magnetic resonance imaging (MRI) technologies which will allow scan times to be reduced from ~1 hour to ~10 minutes in children with diseases in the abdomen. Translation of these rapid paediatric MRI techniques into clinical practise would revolutionize paediatric imaging, improving patient experience, increasing throughput, reducing costs and lowering risk associated with general anaesthesia. It would also improve access to MRI in children, both nationally and internationally, allowing it to be used routinely for diagnosis and follow-up in children with paediatric disease.

These aims will be achieved this through development of optimised MR acquisition strategies combined with Machine Learning (ML) reconstruction techniques. Specific aims include:

1. Development of rapid, undersampled, non-Cartesian sequences for abdominal imaging.
2. Development of ML networks to perform motion correction of data which has been corrupted by respiratory motion, causing artefacts in all areas of abdominal imaging.
3. Development of machine learning techniques for reconstruction of MRI data where only small/limited training data sets may be available: including the use of transfer learning methods and self-supervised learning

Project Approach

To build upon existing rapid 2D and 3D sequences developed in the Cardiac MRI group at UCL/GOSH. Sequence optimisations will be required for abdominal imaging, including optimised temporal/spatial resolution, as well as integration of pre-pulses. This will require close contact with radiologists at GOSH, to ensure that the clinical needs are met.

To collect, curate and use large amounts of prospective and retrospective gold standard pediatric abdominal MRIs acquired in children at GOSH (a radiographer is in place, funded on Dr Steedens UKRI FLF to help with this task). This can then be used to simulate the acquisition (including undersampling artefacts, resolution, and motion artefacts) and used to train machine learning networks.

To optimise machine learning networks for the specific problems described above, in terms of resulting image quality and accuracy. These networks will be integrated into standard clinical workflow to enable clinical validation studies, as well as simple translation into routine clinical practise.

Related Work and Methodological Innovation

Machine learning has become state-of-the-art for some image processing of photographs, including denoising and super-resolution. However, it is only recently that machine learning (ML) methods have been used to reconstruct MR images. We published the first clinical validation of ML for removal of aliases from undersampled 2D dynamic cardiac MRI in children with congenital heart disease in 2019 (Hauptmann A, Arridge S, Lucka F, Muthurangu V, Steeden JA: Real-time cardiovascular MR with spatio-temporal artifact suppression using deep learning–proof of concept in congenital heart disease. *Magnetic Resonance in Medicine*, 2019 Feb;81(2):1143-1156. doi: 10.1002/mrm.27480). We demonstrated this technique can outperform current state-of the-art reconstructions (Compressive Sensing) in terms of image quality and reconstruction time.

We also have performed machine learning super-resolution imaging to significantly reduce scan times for 3D whole heart data (Steeden JA, Quail M, Gotschy A, Hauptmann A, Arridge S, Jones R, Muthurangu V: Rapid Whole-Heart CMR with Single Volume Super-resolution. <https://arxiv.org/pdf/1912.10503.pdf> ).

There remains significant development and optimisation of both MR sequences and ML reconstruction methodology, in order to apply these techniques to other imaging sequences and diseases. There is very little work on using these techniques in the clinical environment, particularly in paediatric diseases.

Strategic Areas:  
The UK is highly regarded as a leader in the development of biomedical technology, and medical imaging is one of the highlighted research areas in the EPSRC Healthcare Technology challenge theme, which was also recognised in the national spending review where Health was one of the few sectors to retain positive funding growth in real terms. The work falls within the "Optimising Treatment" grand challenge and is thoroughly aligned with the "Novel imaging technologies" cross-cutting research capabilities area. The proposed technologies directly satisfy the following key fields of this area:  
- Techniques for image reconstruction  
- Higher performance, novel or lower cost image acquisition technologies  
- High throughput, real-time imaging at the point of care  
- Automated image interpretation to aid clinical decision making

The work is also aligned with the EPSRC Research area, "Medical imaging". In particular, it addresses the high priority areas of this delivery plan:  
- Enabling earlier and more effective diagnosis of physical conditions, to inform treatment planning  
- Novel imaging technologies/modalities that address a demonstrable unmet clinical need and/or offer a significant benefit over current technologies, and have an identified place in the patient pathway

In addition, the Royal College of Radiologists (RCR) has a key policy position statement for establishing frameworks using artificial intelligence (AI) in clinical radiology. This was set up in response to the Prime Minister's challenge to industry and the health sector regarding the development of AI to revolutionise the early detection of disease.

Realisation of this research will ultimately strengthen the UK's position at the forefront of cutting-edge healthcare technologies.

Plan structure

**Project Plan**

Objective



* Demonstrate a clear understanding of project background and aims
* Be able to put forward a concrete work plan with timeline and deliverables

Maximum 2-page long; Arial font; minimum font size 10

Details to include:

* Context and background
* Aims and approach
* Detailed plans w/ timeline and deliverables
* Summary of progress to date

**Je-S form**

Project title

Summary



* 4000 characters max, including spaces and returns
* Sections required
  + Context of the research including potential impact
  + Aims and objectives
  + Novelty of the research methodology
  + Alignment to ESPRC's strategies and research areas
  + Any companies or collaborators involved

Here is a selection of text I had about your project from various bits of UCL paperwork

I think that the current workplan will be around cardiac MRIs (sorry!). The reasons are this are multiple:

* We cannot curate new data because we cannot access the hospital due to COVID
* We cannot collect prospective data because we cannot access the hospital due to COVID
* We have cardiac data curated already, and we also have a framework to benchmark against

So my ideas in terms of workplan would be:

* Install the dlex ML framework developed by Javier - understand what it can do/how is works, how to adapt it and use it etc.
* Get your head around/understand how we can take retrospective MR data and create synthetic MRI data for training
* Run the experiment that we did on the original ML paper yourself - understand the parts, and ensure that everything is working, and the results are similar
* Make some changes to the network and compare the results. This may include:
  + adding a second channel to the network, which includes some prior information about where signal is, to try to regularise the network
  + looking at alternative (sparse) representations of the data (could include temporal or spatial differences of the data, wavelet transform or PCA)
  + investigation of different losses (e.g. an overall loss which includes the spatial information as well as the transformed data)
  + Change of network structure, e.g. to include DENSE blocks, or different depths of network

These concepts will all be useful for the abdominal data, but at least here we know that the problem is solvable and have a benchmark to compare to.

**Project plan First draft**

2 pages size 10 arial

**Demonstrate clear understanding of project background and aims:**

* Context and background:

MRI scans are important in diagnosing diseases of the abdomen in children. Although these can take an hour to perform, and often require the patient to hold their breath for long periods. This means that this type of treatment is only available in specialist centres.

In this time the child may become restless and even small movements in the scanner can worsen results. A way to reduce patient movement is to use General Anaesthetic (GA), although this is expensive and has an associated health risk.

A way to speed up the scan times is to record less data. Although data under sampling creates artefacts which make the images harder to interpret. There are methods to counteract these issues such as Compressive Sensing (CS), but this is a very time-consuming technique.

Machine Learning (ML) has been shown to adequately reconstruct many types of images, although it’s use in MRI image reconstruction is small. In this project we propose to use ML techniques for reconstruction of images from the abdomen of children. This will speed up acquisition times to ~10 minutes as well as producing clear images, useful for clinical staff in their determining diagnoses.

* Aims and approach:

The aim of this study is to reduce Paediatric MRI scan times from one hour down to 10 minutes. This will be achieved via devising novel accelerated MRI technologies which allow children with diseases of the Abdomen to be quickly diagnosed.

Reducing scan times would alleviate the need for GA, improving patient experience. Also, more patients could have scans, reducing costs for the NHS and waiting lists. Moreover, people would have easier access to the scanners worldwide, allowing them to be used more routinely. This could induce health benefits on a broad scale.

These aims will be achieved through the development of novel MR acquisition strategies combined with ML reconstruction techniques. These MR acquisitions will involve performing non-cartesian undersampling of the MR data. The ML reconstruction will account for artefacts caused by respiratory motion. Limited data is available to use, hence our methods will be robust to small amounts of training data. Transfer learning methods and self-supervised learning will be used for this.

Project approach…

**Put forward a concrete work plan with timeline and deliverables:**

* Detailed plans with timeline and deliverables:

*May need some more info on this from Jenny as it covers later years to I believe.*

Over the next weeks I hope to train a network remotely, using the ZCR’s highly powered computers. This will enable me to input data encompassing a greater anatomical region from many more patients. I will visualise artefact removal on a larger scale and adjust parameters to see how these impact results. The aim of this will be to enhance understanding of how retrospective MR data can be used to create synthetic MRI data for training.

In the Journal Club module, I gave a presentation on paper (1). From this work I’ve seen the full cycle of ML, from training and testing a model to inputting in-vivio data into it. The team were able to perform deep-artefact suppression on Cardiac images with greater image quality and shorter reconstruction times than CS reconstructions. I plan to first recreate the work done here by running an ML experiment myself and receiving similar results.

I plan to make changes to the network and compare results with those from the paper. These changes may include:

* Adding a second channel to the network, which includes some prior information about where signal is, to try to regularise the network
* Looking at alternative (sparse) representations of the data (could include temporal or spatial differences of the data, wavelet transform or PCA)
* Investigation of different losses (e.g. an overall loss which includes the spatial information as well as the transformed data)
* Change of network structure, e.g. to include DENSE blocks, or different depths of network
* Summary of progress to date

Up to now I have explored different trajectories of MRI data under sampling. I have explored how under sampling different trajectories induce artefacts into the images in different ways. Also, I’ve looked at how the extent of under sampling in each trajectory effects image quality.

I have trained an ML network which reduces artefacts on a small cardiac dataset. This was done via installing a virtual environment on my computer. I was able to install python and ‘dlex’ packages into here. These allowed me to pre-process the data. This involved temporal interpolation and radial undersampling, allowing aliased Cardiac images to be produced. The under-sampled and fully sampled data were then input to the model allowing it to ‘learn’ parameters to de-alias the image.

* References

[1] - Real-time cardiovascular MR with spatio-temporal artifact suppression using deep learning–proof of concept in congenital heart disease. *Magnetic Resonance in Medicine*, 2019 Feb;81(2):1143-1156. doi: 10.1002/mrm.27480)

**Je-S form first draft**

4000 characters (1 to 2 pages)

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* Summary

*Much of this can be copied from the project summary section above*.

* Context of research including potential impact
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* Novelty of the research methodology
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